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The Response of Consumption to Fuel Switching: Panel Data Estimates

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Abstract

This paper investigates on the extent to which the switching improves households' standard of living. Using a nationwide transition from kerosene to cleaner burning propane in Indonesia, I explore households' consumption response to fuel switching from a nation wide kerosene to liquid petroleum gas conversion program in Indonesia. Based on combustion efficiency and end-use energy equivalence, LPG is cleaner and more efficient than kerosene. Using variation in the timing of the implementation on four waves of the Indonesia longitudinal survey, I compare changes in expenditure within households of targeted districts with changes in expenditure within households of untargeted districts. I find that households reduce their kerosene consumption up to 100% and their fuel expenses are reduced by 40%, or 1.19 USD per month on average. These effects are higher among poor households. I do not find any response to other nondurable expenditures which provides some evidence of consumption smoothing. This is as expected considering the size of the effect is only about a 2% reduction from total monthly expenditure.

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Dirty fuel used in cooking has long been associated with poor health and low productivity. Nonetheless, almost half of the world population is still using it. The desirability to switch to a cleaner fuel depends critically on the extent to which the switching changed households' well being, measured by their consumption. Policies and interventions that targeted on improving household's access to clean cooking energy, including the seventh United Nation's Sustainable Development Goal, have been aggressively trying to tackle this issue. Poor knowledge concerning energy use, consumption pattern, and behavioral response from fuel transition have been translated into uncertainties when formulating this intervention.

Do households improve their standard of living – their consumption – as they switch to more cost effective and cleaner fuel? Using the Indonesia fuel conversion program, I aim to evaluate household response to fuel switching. In 2007, the government of Indonesia ambitiously aimed to encourage more than 70% of all households in the country to switch from kerosene to LPG, a relatively clean, efficient and cost-effective fuel compared to kerosene. The main purpose of this program is to reduce kerosene subsidies, as the government spent almost ten billion USD in 2006 for it. On the consumer side, based on laboratory experiments, one litre of kerone has an end-use energy equivalence of 0.6 kg LPG, under various cooking condition. This program has been successful in increasing the proportion of household who use LPG from 9% to 46%, and decreasing the proportion of household who use kerosene from 42% to 12% (IPUMS, 2013). The reduction on the cost of subsidizing kerosene is claimed to save almost USD 2 billion by May 2010 (Budya and Arofat, 2011).

To conduct this analysis, I use the difference-in-differences estimation strategy on four waves of the Indonesia Family Life Survey. The identification comes from the random variation in the timing of implementation of the program. I focuses on the kerosene consumption, fuel expenditure, utility bills, and other nondurables expenditure as they are likely influenced by households' cooking fuel directly. While households in the treated districts may differ systematically from households in the untreated districts, I show that, within households, expenditure is very similar over time prior to the program. The program is also not correlated with households' main characteristics, which give some indication that there are no subsequent changes that might lead to spurious results. Note that the estimation captures partial equilibrium effect as it only captures the changes in spending correlated with the program timing. The ultimate impact of the program on aggregate consumption could be higher or lower than my estimation, due to multiplier effects and possible changes in prices.

I find that households reduce their kerosene consumption up to 100%. Household utility bills are reduced by 40%, 1.19 USD per month, on average. This response is statistically and economically significant, especially for the poor households. Fuel expenses takes about 30% of household utility bills, on average, with substantial heterogeneity across income brackets. This estimate is consistent with several small surveys conducted after the program (Budya and Arofat, 2011; Andadari et al., 2014). I do not find any response to other nondurable expenditures which provides some evidence that, in this setting, consumption does not change in response to expected variations in fuel expenditure. Although this paper does not test any particular theoritical model, the results support rational expectation life-cycle theory which implies no spending response to a predictable change in anticipated changes in resources.

This paper is structured as follows. Section I describes the policy context of energy transition and its potential economic impact. Section II describes the IFLS data and main baseline characteristics, and Section III sets my empirical methodology and relevant validity test. Section IV presents the main results regarding household's response to the fuel switching, and how it differs across households' characteristics. Section V concludes.

1 Policy Context

How clean energy transition influence household total energy consumption? Does household transition to a more cost effective cooking fuel reduce their total energy expenditure? Do households smooth their consumption during the transition. These questions are fundamental in designing interventions that support a sustainable energy transition, considering that cooking fuel plays an important role in household's well being (Duflo et al., 2008).

The Seventh Sustainable Development Goal emphasizes on affordability, reliability and sustainability of modern energy for all by 2030. In 2014, the access to clean fuels has climbed slowly from 51 per cent in 2000 to 58 per cent in 2014 (Economic and Council, 2016). Today, in the world, there are still more than 3 billion people, mainly in Asia and sub-Saharan Africa, are still cooking without clean fuels and more efficient technologies. Policy reports have increasingly associated the use of dirty fuel with mortality and burden of disease (Zhang and Wu, 2012). Hence, policy makers, donors, and international organization have put this issue into their priority.

In 2005, more than 80% of household in Indonesia is still using dirty fuel for cooking, mainly wood fuel and kerosene. Government highly subsidizes kerosene, known as a cleaner fuel compared to wood fuel, to incentivice households to shift from wood fuel. Inevitably, it triggers unintended use of the fuel by reselling the fuel to industries or abroad. Indonesian Government started to subsidize other cleaner, LPG, and limit the supply of kerosene.

1.1 Large Scale Fuel Switching

Indonesia, the world's fourth-most-populous country, with 243 million people, has been subsidizing the retail price of cooking fuels since 1967 (Dillon et al., 2008). As in 1980s Indonesia's oil production is high, fuel subsidies were affordable. But domestic energy consumption of Indonesia has surged by more than 50% over the past decade. Moreover, the increase in global our prices has increase the subsidy cost more than 4 billion USD in 2007. In response to this, in 2007, Indonesian government launched Kerosene to LPG Conversion Program [1].

The main purpose of this conversion program was to reduce the amount of government

[1] http://prokum.esdm.go.id/perpres/2007/perpres_104_2007.pdf

subsidy on kerosene.[2] The cost to provide LPG is lower than kerosene[3] and its infrastructure is also more available compared to other alternatives, such as natural gas and electricity. The government aimed to convert 73% of households who use kerosene[4] to LPG. Households who use kerosene primarily and have not use LPG before were eligible in the program. They would received a free LPG stoves along with one 3-kilo LPG cylinder. Having this specific type of cylinder makes them also eligible to refill it under subsidized price. The implementation is gradual over time and homogenous across districts. The Ministry of Energy and Mineral Resources selects the treated districts in a given fiscal year based on each district's level of kerosene usage, LPG infrastructure readiness, location and size of the area. Seven years later, there is a decrease in the percapita fuel expenditure but only among those that got the program (Figure 1). As can be seen, the distribution for households in the treatment group and in the control group are very similar prior to the program. After the program, there is a big shift to the left which reflects the reduction in the fuel expenditure.

1.2 Potential Economic Impact of Fuel Switching

Existing studies on the impact of energy transition has largely focused on health issues, as burning dirty fuel produces indoor air pollution that has adverse impact on health and productivity (Duflo et al., 2008; Graff Zivin and Neidell, 2012). Those studies largely based on observational studies. Indeed, we have very limited evidence on the causal impact of fuel switching, especially on economic outcomes such as energy consumption pattern, adult labor market productivity, child school attendance, and medical cost. For example, when household members use more efficient fuel for cooking, they might cook faster and burn less fuel. They would consume less, thus have lower total energy expenditure. They might also consume more, considering that now cooking is more convenient. If there is any changes in energy expenditure, will households tend to smooth their consumption by spending the extra money for some other consumption. Some other possibility is that using cleaner fuel also save time from fuel collection, cleaning up kitchen and stove, which then enable households' hours available towards income-generating purposes. These potential effects are mixed and difficult to disentangled in a structural framework. Hence, this paper focuses on the empirical evaluation of the average treatment effect on household consumption due to fuel switching policy.

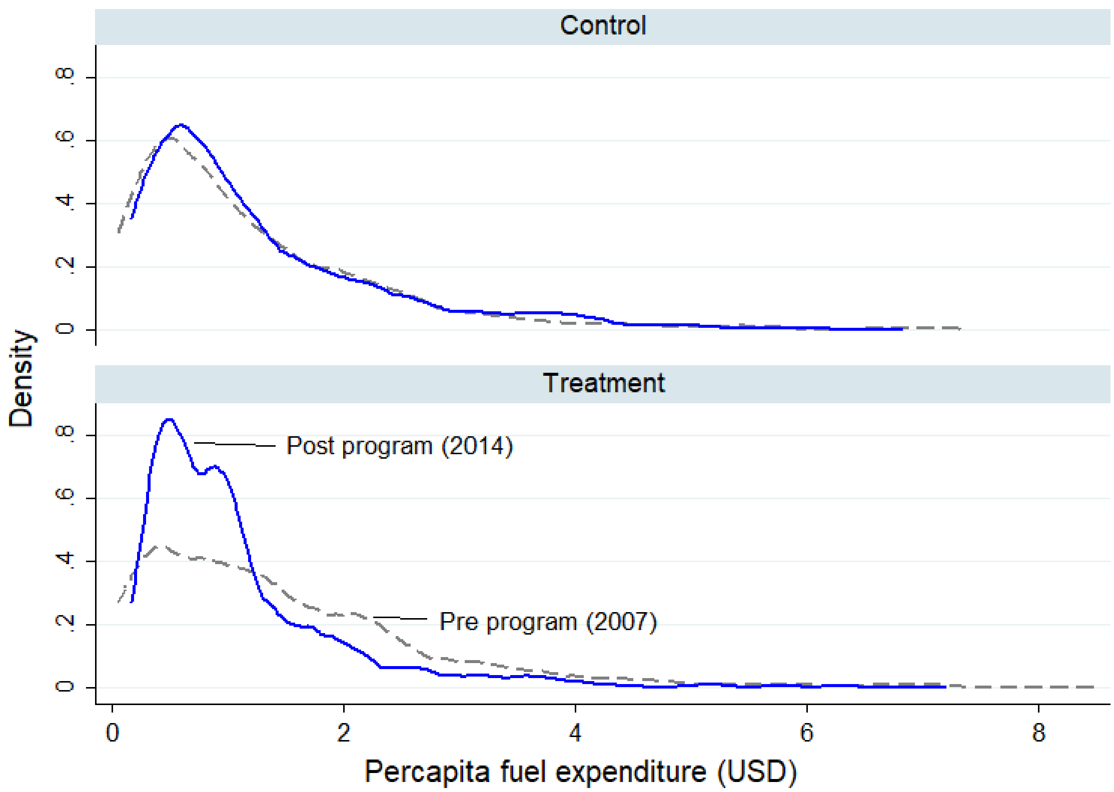
Relevant studies measuring reactions to changes in resources are usually linked to consumption smoothing and the permanent income hypothesis. The program is implemented gradually and goes through various stages and thus households certainly aware of its occurrence. Given that there are many ways in which households are likely to have responded to change in household energy mix, it will be difficult to predict with much confidence what the combined impact in household consumption is likely to be in the presence of any subsequent multiplier,

[2] Some other purposes and the detail of the program are discussed in (Budya and Arofat, 2011).

[3] Subsidizing kerosene cost 25% (0.17 USD/liter) higher than subsidizing LPG (see Andadari et al. (2014)).

[4] 42 millions from 57 total households in 2007

Figure 1: Density of percapita fuel expenditure before and after the program



Notes: This figure shows the density curve of percapita fuel expenditure for treatment and control group before and after the program. The treatment group is households who reside in the district that get the program before 2011 and the control group is households who reside in the district that get or not yet get the program after 2011.

and how those impacts are likely to vary across socio-economic and demographic groups. In the absence of empirical evidence in the past studies, this paper focuses on households' consumption smoothing over an anticipated change in energy mix.

Many studies have put a lot of emphasize on wood fuel. Kerosene is the only cooking fuel product consumed by the low-income households in urban population, and the second after wood in rural population. While the cost of subsiding it is high, it is claimed as an ineffective social policy as there are many cases of unintended use of kerosene subsidy (Mills, 2017). On the health side, WHO is no longer classifying kerosene as clean fuel, and discourage the use of it instead (WHO et al., 2012) as burning kerosene has been found to be as bad as wood fuel (Saksena et al., 2003). Hence, this study fills the gap in the literature by discussing the impact of a decreasing use of kerosene and an increasing use of LPG.

2 Data and Summary Statistic

2.1 IFLS

I employ four waves of the Indonesian Family Life Survey (IFLS), a longitudinal survey carried out by the RAND corporation (Thomas et al., 2012) that were carried out in 1997, 2000, 2007, and 2014 respectively. IFLS is known as one of the best longitudinal data with a very low level of attrition due to its successful follow-up rates despite of the mobility of the respondents and it represents 83% of the Indonesian population living in 13 of out of 26 provinces. The data contains a great amount of information at individual, household and community level on a large array of economic, social and labor supply characteristics. I focus on consumption and expenditures measurements to measure the well being of households.

2.1.1 Consumption measurements

Firstly, I use quantity of kerosene from the recent purchase and the unit price of kerosene from the last purchase as the outcome variables, considering that the program has a direct influence in kerosene availability in the market. The survey asks "within one month recall period, the last time you purchased kerosene, what was the quantity you purchased?". Note that this variable does not capture the total quantity of kerosene use by households, but rather the sum of one time purchase at one time by all household's members, during last week preceding the survey.

Then, to look at how households' response to the program, I use expenditure on nondurables in a given period as a preferable measure of consumption, following Browning and Lusardi (1996). The outcome variables are a series of subcategories of monthly nondurable expenditures: (1) utility bills, which includes fuel, electricity, water and telephone expenses; (2) food, which includes food/products bought/consumed by all the members of household, food consumed away from home, and cigarettes and tobacco; (3) other strictly nondurables[5], excluding item (1).

Changes in utility bills or food expenditures might alter the marginal utility of consumption from other nondurable goods. If this is true, then the effect on nondurable expenditure is For example, households invest in This would be true if, change I exclude those to allow separate analysis for each component. It is reasonable to assume that changes in expenditures for food and utilities is inelastic and separable in utility from other consumption. In addition, these component account for a significant share of a typical household budget, thus the variation is economically meaningful. Note that fuel expense in the utility bills is a different category from fuels for transportation. All expenditures are in monthly and percapita real terms (adjusted with 2007 Consumer Price Index).

IFLS uses an up to one month recall period, in which households was asked about their last purchase history for high frequency items such as food and fuel, and up to a year for

[5]This category follows Browning and Lusardi (1996), which excludes apparel, medical services, and education expenses

low frequency expenditure such as health. The respondent is asked to recall the food items purchased, self-produced, or received from another source during the last week. For expenses like utilities, transportation, and domestic services, the reference period is the past month. The reference period for medical and education expenditures is the past year. The question is formulated as follows: "How much money was spent for non-food items during the past month?" Responses are collected based on the month of interview. This is not a trivial issue given the importance of seasonal effects in consumption processes. Hence, for robustness, I include a model that uses month-year fixed effects.

2.2 Program Implementation

Ministry of Energy and Mineral Resource decides the order in which districts are treated. Pertamina, a State-Owned energy company, implements the program based on the given order. It is noted that the program is targeted based on the district's kerosene consumption which might be correlated with some other district's characteristics which then lead to household sorting. While non-randomization is acknowledged, my empirical analysis will focus on comparing households in district that are treated to other initially similar households in districts that have not yet treated that might otherwise behave in the similar way. Table 2.1 shows total households in the sample and number of unique districts in the sample based on the program year. Later in the analysis, I classify the treatment group is households who reside in the district that get the program before 2011 and the control group is households who reside in the district that get or not yet get the program after 2011. For robustness checks, I consider some alternative for the control group.

Table 2.1: Total sample by program implementation year

	Program Implementation Year		
	2007-2010	2011-2013	>2013
Total Households	16,226	2,908	960
Total Districts	147	39	9

Source: Pertamina

2.3 Average Household Characteristics and Baseline Differences

Table 2.2 shows the key descriptive statistics of the data before the program. I report the average values and its standard deviation of households' characteristics in the control group, weighted with the survey weights, in column 1 and 2. In column 3 and 4, I report the average values and its standard deviation of households' characteristics in the treatment group, weighted with the survey weights. In column 5 and 6, I report the within-household difference between the average values of the treatment and the control households at baseline, controlling for household fixed effects and province-year dummies.

Primary cooking fuel. On average at the baseline years, about 30%-43% of households are using kerosene as their main cooking fuel, while 45%-68% of households are using wood as their main cooking fuel. There are very few households use either LPG or electricity. The trend to use these fuels between treatment and control group are very similar as shown in column 5.

Households characteristics. Households size is three on average, with total monthly expenditure around 70 USD. About 40% is spent on food and 8% is spent on the utility bills. Total working hours for all households members are around 23 hours per week. Average last year income, an estimate for household members that worked last year and for whom respondent knew earnings of last year, is 300 USD, or 25 USD per month. Average yearly income during the survey year is calculated from reported monthly salaries, about 130 USD, which are consistently about two of the fifth of reported last year income. More than 80% of households own their house and do not move.

3 Empirical Methodology

I use difference-in-differences estimation strategy to exploit variation across time of program implementation on household level panel data, following Eq. 1.

$$C_{hrt} = \beta_{1h} + \beta_{2t} + \beta_3 P_{r2014} + \beta_4^{'} X_{ht} + \epsilon_{hrt} \tag{1}$$

where h indexes households, r indexes district, and t indexes year of survey, C is household consumption or their log; α_h, β_{1c} are household, and time fixed effects. Following the literature, I add 1 if the dependent variable is zero before taking log transformation. X_{ht} is a set of covariates that capture household characteristics (age, family size, interview month and year). P_{r2014} is a dummy of the program implementation, that is the interaction between treated district and year of 2014. Using a dummy variable for the program implementation guards against measurement error. I use ordinary least squares and cluster the standard errors by district to allow for heteroskedasticity and serial correlation in within district as the implementation of the program is varied by district.

Key coefficient of interest is β_3 which measures the average response of household consumption to the program implementation. This reduced form effect contains two components: substitution effects and income effects. Substitution effects arise when the prices of kerosene increase due to removal of the subsidy, and households will substitute towards other fuel alternatives as they become relatively cheaper than kerosene. Income effects arise when the lower effective price for other alternative fuels increases household's purchasing powers, leading to a further increase in consumption of those alternative fuels (assuming it is a normal good) and other normal goods consumption.

The main empirical challenge is that households in the treated districts may differ systematically from households in the untreated districts, that is the timing of program implementation might have been associated with unobserved factors that otherwise influence households consumption trend in the targeted districts. To address this issue, first, I show that the

Table 2.2: Baseline Household Characteristics Before the Program

	Control group (N=2,930)		Treatment group (N=12,199)		Within-HH differences	
	Mean	SD	Mean	SD	Mean	SE
	(1)	(2)	(3)	(4)	(5)	(6)
Primary cooking fuel:						
Electricity	0.00	0.05	0.00	0.07	0.02**	(0.01)
LPG	0.01	0.11	0.11	0.32	0.03	(0.03)
Kerosene	0.29	0.46	0.43	0.50	-0.02	(0.05)
Wood	0.68	0.46	0.45	0.50	-0.02	(0.04)
Percapita kerosene (litre)	1.68	7.32	1.34	6.03	-0.12	(0.46)
Kerosene price (USD)	0.2	0.53	0.16	0.3	-0.11	(0.20)
Household characteristics:						
Husband age	36.90	22.06	38.82	21.69	-0.34	(1.85)
Wife age	41.00	14.61	41.50	14.94	-0.55	(1.26)
Household size	2.92	1.32	3.01	1.34	-0.03	(0.11)
Number of adults	0.33	0.56	0.29	0.52	-0.10	(0.07)
Number of children	2.41	1.17	2.52	1.22	-0.02	(0.10)
Number of elderly members	0.02	0.15	0.02	0.16	-0.00	(0.01)
Use electricity	0.84	0.36	0.92	0.27	-0.14*	(0.08)
Own house	0.86	0.34	0.87	0.34	0.00	(0.04)
Have fridge	0.16	0.36	0.17	0.37	0.02	(0.06)
Boil water to drink	0.83	0.38	0.93	0.26	-0.03	(0.07)
Did not move	0.75	0.43	0.88	0.33	-0.03	(0.18)
Percapita total expenditure (USD)	72.13	315.13	71.42	381.76	17.57	(17.30)
Percapita non-durables (USD)	57.25	284.38	58.47	360.54	18.09	(15.49)
Percapita food exp. (USD)	31.04	25.86	28.99	49.40	3.28	(3.06)
Percapita utility bills (USD)	6.58	124.50	10.87	159.93	11.70	(12.56)
Working hours per capita/week	23.08	18.95	23.41	19.23	-5.06**	(2.13)
Percapita last year income (USD)	302.99	431.12	281.37	617.36	-99.95	(68.15)
Percapita this year income (USD)	129.10	296.46	138.46	464.67	-11.01	(24.51)
Head of household:						
Female	0.16	0.37	0.15	0.35	-0.03	(0.03)
Uneducated	0.12	0.32	0.13	0.33	0.02	(0.02)
High school educated	0.81	0.39	0.81	0.39	-0.00	(0.03)
Diploma or higher	0.07	0.25	0.06	0.24	-0.02	(0.01)
Worked last year	1.21	0.61	1.22	0.63	0.07	(0.08)

Notes: All regressions use the sample prior to the program. Control group is households living in the districts that get the program after 2011 (less than three years). Treatment group is househoolds living in the district that get the program during 2007-2010. In column 1 and 2, I report the average values and its standard deviation of control households at baseline. In column 3 and 4, I report the average values and its standard deviation of the treatment households at baseline. Each row in column 5 and 6 is the estimated differences from a regression of each household characteristic on an indicator variable whether the households are in the treatment group, controlling for household fixed effects and province-year dummies. The standard error is clustered by district. 1 USD = Rp 13,000.

pre-implementation trends in consumptions between treatment and control groups are very similar. In Table 3.1, I show regression coefficient of each outcome variable on the district and year dummies. Table 7.1 in appendix confirms that the results are very similar, with or without household fixed effects. In other words, households in the treatment and control groups are very similar before the program on their percapita kerosene quantity, nondurable expenditure and their utility bills. They also face similar price of kerosene.

Table 3.1: Test of parallel time trends

	(1) Strictly non-durables	(2) Food	(3) Utility bills	(4) Trans-portation	(5) Rotating savings	(6) Household expenses	(7) Personal toiletries
Panel A							
ProgramX2007	0.261*	0.128	0.123	0.728	0.066	0.211	0.291
Standard error	(0.142)	(0.109)	(0.294)	(0.827)	(1.036)	(0.215)	(0.312)
Obs.	15,058	15,097	15,097	15,097	15,097	15,097	15,097
R-squared	0.642	0.599	0.579	0.505	0.612	0.407	0.448
	(8) Servants' wages	(9) Sweeptakes	(10) Monthly expendi-ture	(11) Durables	(12) Medical	(13) Last year income	
Panel A							
ProgramX2007	0.265	-0.002	0.287**	1.017***	-0.542	0.418	
Standard error	(0.197)	(0.094)	(0.144)	(0.385)	(0.433)	(0.531)	
Obs.	15,097	15,097	14,995	15,097	15,097	15,129	
R-squared	0.499	0.353	0.666	0.524	0.455	0.548	

Sample is prior to the program. All regressions include district fixed effects and month-year dummies. The standard error is clustered by district.

Secondly, a probit for being in the treatment group against a variety of observable characteristics did not reveal any strong systematic correlations (Table 3.2). This result is consistent with (Andadari et al., 2014; Imelda, 2018) which study the same program. They show that the program induced by the program has been largely independent of household characteristics. Although households in the treatment group shows that they are more likely to have less household members, this is actually driven by the increase in household members in the control group. There is also a weak correlation that households with less uneducated members are likely to be in the treatment group, the coefficient are very small, 5%. Overall, there is little evidence on any systematic difference between households in the treatment group and the control group. For the robustness checks, I include these control variables and the main conclusion stays.

To some extent, the results from Table 3.1 and Table 3.2 help to address some concern about possibly unobserved shocks that might be correlated with household's consumption. Thus, in further analysis, I consider that the control group as a valid counterfactual for the treatment

Table 3.2: Is the program correlated with the observables?

	(1) Husband age	(2) Wife age	(3) Household size	(4) Number of adults	(5) Number of Children	(6) Use electricity	(7) Own house	(8) Have fridge	(9) Boil water to drink
ProgamX2014	-1.25	-1.32	-0.36***	-0.29***	-0.01	-0.07	0.01	0.01	-0.01
	(1.860)	(1.039)	(0.107)	(0.099)	(0.070)	(0.054)	(0.023)	(0.049)	(0.064)
Obs.	20,094	20,094	20,094	20,094	20,094	20,094	20,094	20,094	20,094
R^2 stat	0.573	0.570	0.506	0.470	0.302	0.576	0.568	0.566	0.460

	(10) Did not move	(11) Percapita food exp.	(12) Percapita income	(13) Female	(14) Uneducated	(15) High school educated	(16) Diploma or higher	(17) Worked last year
ProgamX2014	-0.01	-1.88	-23.50	-0.00	-0.05**	0.03	0.02	-0.00
	(0.121)	(2.578)	(93.590)	(0.036)	(0.024)	(0.038)	(0.021)	(0.085)
Obs.	20,094	20,051	20,094	20,094	20,094	20,094	20,094	20,086
R^2 stat	0.424	0.364	0.451	0.598	0.671	0.671	0.757	0.455

Each column reports the estimated differences from a regression of each household characteristic on an indicator variable whether the household is in treated region, controlling for household fixed effects and province-year dummies. Column 1 - 13 report the main household characteristics. Column 14 - 17 report the head of household characteristics. The standard error is clustered by district.

group in the absence of the program, conditional on household fixed effects, district-year fixed effects, and the other time-varying household characteristics.

4 Estimated Impacts of Fuel Switching

I begin the analysis by estimating the average program effect using full sample. Using different timing of the program, I refine my identification strategy subsequently using alternative treatment and control groups by exploiting: (1) comparing only early treated districts with the untreated districts, (2) comparing only the late treated districts with the untreated districts, (3) comparing only treated districts.

4.1 Variation across all households

The program effect on quantity and price of kerosene. Table 4.1 show that percapita kerosene quantity in the last purchase one month preceding the interview (column 1-4) and log kerosene price per litre (column 5-8). After the program, households no longer buy kerosene and kerosene price is increased up to 70% due to the program. Note that the sample is significantly reduced to 15,193 observations for the kerosene quantity and to 9.169 for kerosene price, due to missing values.

The program effect on primary cooking fuel. I present the effect of the program on household's primary cooking fuel choice in Table 4.2. Column 1-4 indicate the independent variable, which is a dummy variable of household's cooking fuel. It shows that the program significantly

Table 4.1: Effect of the program on kerosene quantity and price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Percapita Kerosene Quantity (litre) Mean: 0.93 litre per one time purchase				Log (Kerosene Price) Mean: 0.19 USD/ litre			
ProgamX2014	-1.560***	-1.408***	-1.409**	-1.831***	0.338***	0.263***	0.277***	0.337***
	(0.499)	(0.350)	(0.586)	(0.683)	(0.033)	(0.026)	(0.045)	(0.078)
Observations	15,153	15,153	15,153	15,153	9,136	9,136	9,136	9,136
R-squared	0.038	0.023	0.356	0.354	0.148	0.146	0.579	0.570
District FE	Y				Y			
Prov. X Year FE		Y	Y			Y	Y	
Household FE			Y	Y			Y	Y
Interv. Month FE				Y				Y

Each column reports the estimated differences of percapita kerosene quantity in the last purchase one month preceding the interview (column 1-4) and log kerosene price per litre (column 5-8) due to the program, controlling for household fixed effects and province-year dummies. The standard error is clustered by district.

increases the probability of using LPG and reduces the probability of using kerosene by 50%. The program has no effect in the use of electricity and wood fuel. The magnitude is slightly higher compared to the estimates in (Imelda, 2018), considering that it accounts for household fixed effects.

Table 4.2: Effect of the program on primary cooking fuel

	(1)	(2)	(3)	(4)
	Primary cooking fuel:			
	Electricity	LPG	Kerosene	Wood
ProgamX2014	0.00	0.45***	-0.50***	0.05
	(0.00)	(0.07)	(0.07)	(0.04)
Observations	20,094	20,094	20,094	20,094
R-squared	0.26	0.68	0.61	0.70
Treated Mean	0.00	0.27	0.32	0.40

Each column reports the estimated differences from a regression of dummy variables of primary cooking fuel on the treatment dummy, controlling for household fixed effects and province-year dummies. The sample size is 20,140. The standard error is clustered by district.

The program effect on nondurable expenditures. Table 4.3 shows the estimated program effect on the propensity to spend on subcategories of monthly expenditure. The dependent variables are all log transformed percapita monthly expenditure. Each Dependant variable is indicated on each column. The utility bills in column 3 includes fuel, electricity, water and telephone. Transportation column 4 includes bus fare, cab fare, vehicle repair costs, fuel and the like. Rotating savings club in column 5 is known as *arisan*. Household items in column 6 includes laundry soap, cleaning supplies, anti-mosquitoes and the like. Personal toiletries in column 7 includes soap, shaving supplies, cosmetics and the like. Sweepstakes in column 9 includes lotteries, and the like. Total monthly expenditure in column 10 is the aggregate monthly expenditure which is the sum of column 1-9. All regressions use households and month-year fixed effects. The mean dependent variable is percapita monthly expenditure in USD.

The program reduces households' utility bills by 70%, or about 6 USD per month. By switching to LPG, households also reduce their cleaning expenses up to 70% (in column 6 and 7), or about 2 USD per month in total. With cleaner fuel like LPG, it is possible that the kitchen would be cleaner and the households members who do the cooking do not need to clean the kitchen or themselves as often as when they use kerosene. The transportation expenditure is decrease, likely because in some cases, kerosene can be mixed with gasoline used in transportation. Since kerosene is limited, this reduction could reflect the reduction in kerosene usage. I do not see any effect on any other subcategories of monthly expenditures.

Table 4.4 shows the estimated program effect on the propensity to spend on categories of yearly expenditure as well as weekly working hours. The dependent variables for column 11-15 are log transformed percapita yearly expenditure and for column 16 is percapita working hours per week. All regressions use households and month-year fixed effects. The mean dependent variable is percapita expenditure in USD or working hours per week.

Where does the reduction in the expenditures is spent on? I do not see any increase in other expenditure categories which might indicate that since the 'savings' are small compared to the total expenditure, households might distribute this small savings equally to other expenditures without noticing it. To some extend, these results support the consumption smoothing hypothesis.

Effect of the program on each component in utility bills. Table 4.5 reports the estimate of each component of the utility bills. The dependent variables used in each column are log percapita monthly expenditure on fuel (column 1-2), electricity (column 3-4), water (column 5-6) and telephone (column 7-8). Model 1, 3, 5, and 7 capture the regression coefficient within district, while model 2, 4, 6, and 8 capture within household, controlling for the interview month. Note that the sample uses only IFLS 2007 and 2014, since only the last two surveys break down the utility bill components.

Fuel expense is the main share in the utility bill, and it is the main driver of the reduction in households' utility bills. The fuel expense declines by about 40%, about the same magnitude as the declines in the total utility bills. There are some reduction in the electricity expense as well, which could indicates that households might shift from cooking with electricity, to cooking with LPG. Water expense is increase, but the sample size is significantly smaller due to missing data.

The estimates shows that the program reduces household fuel expenses by 1.19 USD. The magnitude of the effect is within the same range as several surveys conducted within small sample size, up to 1.64 USD (Andadari et al., 2014; Budya and Arofat, 2011). The electricity expense is increase about 13%, although not statistically significant, in contrast with Andadari et al. (2014) findings that the conversion program led to an increasing consumption of both electricity and traditional biomass as households are stacking fuels.

Table 4.3: The propensity to spend on subcategories of monthly expenditures

	(1) Strictly non-durables	(2) Food	(3) Utility bills	(4) Transportation	(5) Rotating savings
ProgramX2014	-0.535	0.017	-0.704***	-0.687**	0.403
Standard error	(0.505)	(0.089)	(0.187)	(0.344)	(0.556)
Obs.	19,935	20,051	20,051	20,051	20,051
R-squared	0.418	0.539	0.490	0.450	0.542
Mean dep. var.	5.06	31.28	8.75	5.9	2.41

	(6) Household expenses	(7) Personal toiletries	(8) Servants' wages	(9) Sweeptakes	(10) Total exp.
ProgramX2014	-0.497***	-0.692***	0.480	0.009	-0.071
Standard error	(0.161)	(0.202)	(0.310)	(0.053)	(0.099)
Obs.	20,051	20,051	20,051	20,051	19,886
R-squared	0.319	0.367	0.446	0.276	0.628
Mean dep. var.	1.49	1.87	0.91	0.41	74.77

Notes: The dependent variables are all log transformed percapita monthly expenditure. Each Dependant variable is indicated on each column. The utility bills in column 3 includes fuel, electricity, water and telephone. Transportation column 4 includes bus fare, cab fare, vehicle repair costs, fuel and the like. Rotating savings club in column 5 is known as *arisan*. Household items in column 6 includes laundry soap, cleaning supplies, anti-mosquitoes and the like. Personal toiletries in column 7 includes soap, shaving supplies, cosmetics and the like. Sweepstakes in column 9 includes lotteries, and the like. Total monthly expenditure in column 10 is the aggregate monthly expenditure which is the sum of column 1-9. All regressions use households and month-year fixed effects. The mean dependent variable is percapita monthly expenditure in USD. 1 USD = Rp 13,000.

Table 4.4: The propensity to spend on categories of yearly expenditures and weekly working hours

	(11)	(12)	(13)	(14)	(15)	(16)
	Yearly expenditure					Per week
	Education	Charity	Medical	Durables	Last year income	Working hours
ProgramX2014	-0.535	-0.133	-0.493	0.115	-0.837	3.671
Standard error	(0.505)	(0.278)	(0.600)	(0.403)	(0.633)	(2.429)
Obs.	19,935	20,051	20,051	20,051	20,094	20,094
R-squared	0.418	0.371	0.378	0.454	0.439	0.486
Mean dep. var.	5.06	29.19	16.3	80.21	301.65	23.42

The dependent variables for column 11-15 are log transformed percapita yearly expenditure and for column 16 is percapita working hours per week. All regressions use households and month-year fixed effects. The mean dependent variable is percapita expenditure in USD or working hours per week. 1 USD = Rp 13,000.

Table 4.5: Effect of the program on each component in utility bills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fuel exp.		Electricity exp.		Water exp.		Telephone exp.	
ProgamX2014	-0.455***	-0.439**	-0.154*	-0.134	0.013	0.248*	0.101	0.054
	(0.136)	(0.182)	(0.087)	(0.145)	(0.074)	(0.146)	(0.076)	(0.147)
Obs.	8,443	8,443	9,104	9,104	2,835	2,835	6,660	6,660
R^2 stat	0.133	0.682	0.238	0.802	0.377	0.895	0.176	0.776
District FE	Y		Y		Y		Y	
Household FE		Y		Y		Y		Y
Mean dep. var.	2.71		5.77		1.73		16.96	
Month FE		Y		Y		Y		Y

Each column reports the estimated differences from a regression of log percapita monthly expenditure on fuel (column 1-2), electricity (column 3-4), water (column 5-6) and telephone (column 7-8) on the treatment dummy. Model 1, 3, 5, and 7 capture the regression coefficient within district, while model 2, 4, 6, and 8 capture within household, controlling for the interview month. The standard error is clustered by district. The sample uses only IFLS 2007 and 2014 which are the only two survey that breakdown the utility bills component.

4.2 Timing of the program

Here, I explore if the results are differ by the duration of the program. I classified households who are treated in 2007-2010 as early treated group and households who are treated in 2011-2013 as late treated group. Panel A in Table 4.6 shows the pre-implementation period, and Panel B shows the program effect based on the alternative treatment and control groups.

Table 4.6 shows coefficient estimates β_3 from Eq. 1 with different sets of treatment and control group. As the treatment group, column 1-2 and 5-6 use early treated households, and column 3-4 use late treated households. As the control group, column 1-4 use untreated households, and column 5-6 use late treated households. Panel A uses sample prior to the program to show pre-implementation trend between treatment and control groups. Panel B uses full sample to look at the program effect on the log utility bills.

The program effect on the utility bills for early treated households are very similar with earlier estimation in Table 4.3 column 3. On the other hand, the reduction in the utility bills for late treated households are only about half of the earlier result, 26%. This is as expected considering that the program is implemented gradually. Table 4.6 in Appendix confirm that the reduction in kerosene purchased is less precise when I compare late treated group as the control and untreated groups as the control.

4.3 Differences in responses across households

Following the literature, for each variable, I split households into three groups by percapita household yearly expenditure: below 33th percentile, below 66th percentile and above 66th percentile. Table 4.7 shows the estimated differences on each subcategories of expenditure by the groups with income below 33th percentile (column 1-4) and income above 66th percentile (column 5-8), controlling for household fixed effects and month-year interview date dummies. The outcome variables are a log transformation of percapita monthly expenditure stated in

Table 4.6: Effect of the program with alternative control groups on utility bills

	(1)	(2)	(3)	(4)	(5)	(6)
	Early vs Untreated		Late vs Untreated		Early vs Late Treated	
Panel A. Before the program						
ProgramX2007	-0.034	0.010	0.008	0.089	-0.044	-0.034
Standard Error	(0.091)	(0.115)	(0.117)	(0.176)	(0.080)	(0.098)
Obs.	8,589	8,589	1,884	1,884	9,594	9,594
R^2 stat	0.381	0.800	0.396	0.833	0.374	0.798
Panel B. Full sample						
ProgamX2014	-0.388***	-0.409***	-0.328***	-0.264**	-0.057	-0.061
Standard Error	(0.094)	(0.115)	(0.106)	(0.126)	(0.053)	(0.063)
Obs.	12,654	12,654	2,794	2,794	14,135	14,135
R^2 stat	0.384	0.739	0.395	0.758	0.377	0.736
District FE	Y		Y		Y	
Household FE		Y		Y		Y
Month FE		Y		Y		Y

As the treatment group, column 1-2 and 5-6 use early treated households, and column 3-4 use late treated households. As the control group, column 1-4 use untreated households, and column 5-6 use late treated households. Panel A uses sample prior to the program to show pre-implementation trend between treatment and control groups. Panel B uses full sample to look at the program effect on the log utility bills (β_3 coefficient from Eq. 1). The standard error is cluster by district.

each column.

The effect of the program is larger for 'poor' households, although there is a large standard error for the effect of the program on the utility bills. In total the reduction in the expenditure is larger for 'richer' households. For the transportation expenditure, there are no significant effect on both groups.

5 Robustness

5.1 Fuel stacking

Fuel stacking is common. In general, households tend to stack fuels rather than moving away from previously used fuels when adopting a new fuel (Jeuland et al., 2015). Figure 2 is consistent with this argument. Before the program, households who use kerosene as their main cooking means, on average, bought about two litre of kerosene. Other households, who use other cooking means, bought about one litre of kerosene, on overage. This fuel mix is often unrecorded in the national survey data and using dummies for primary cooking fuel does not capture the actual fuel consumption very well. But IFLS includes measures on quantity and prices for kerosene purchase starting from the year 2000. Thus, in the next section, I discuss the impact on kerosene quantity and kerosene price.

5.2 Falsification

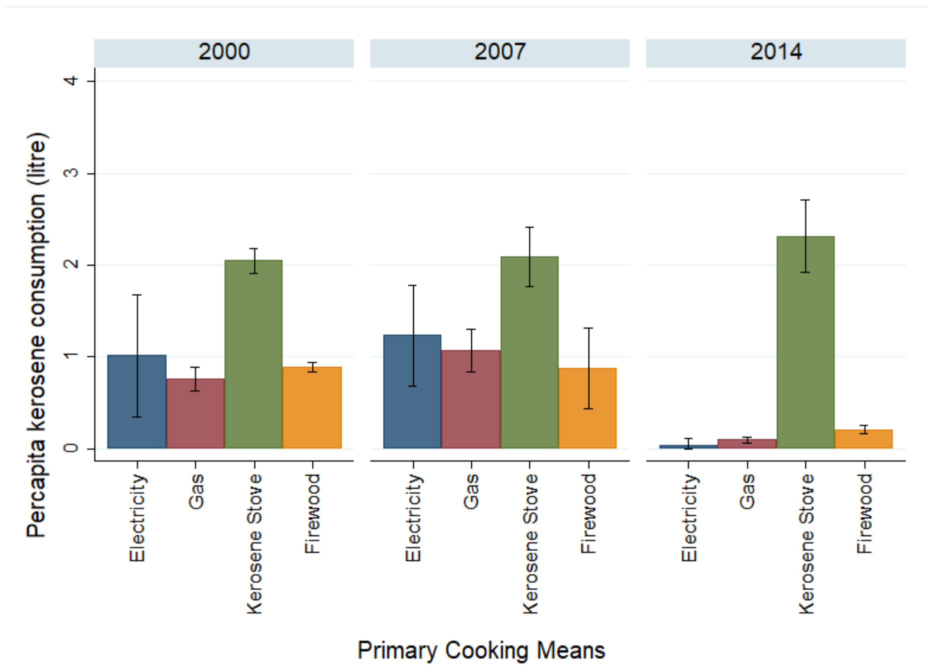
Some concurrent changes might happen within the same time as this program. A clear example would be 2007-2008 global financial crisis. The concern is that the effect of the crisis contaminate

Table 4.7: Effect of the program across different households

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Below 33th percentile				Above 66th percentile			
	Utility bills	Household expenses	Personal toiletries	Transportation	Utility bills	Household expenses	Personal toiletries	Transportation
ProgamX2014	-0.868	-0.612	-0.881**	0.263	-0.635**	-0.387	-0.400	-0.168
	(0.625)	(0.406)	(0.341)	(0.911)	(0.289)	(0.587)	(0.415)	(0.539)
Standard error								
Observations	6,629	6,629	6,629	6,629	6,628	6,628	6,628	6,628
R-squared	0.571	0.536	0.551	0.584	0.673	0.503	0.542	0.607
Mean dep. var.	1.11	.34	.34	.54	22.76	3.53	4.64	15.41

Notes: Each column reports the estimated differences on each subcategories of expenditure by the groups with income below 33th percentile (column 1-4) and income above 66th percentile (column 5-8), controlling for household fixed effects and month-year interview date dummies. The outcome variables are a log transformation of percapita expenditure stated in each column. The standard error is clustered by district.

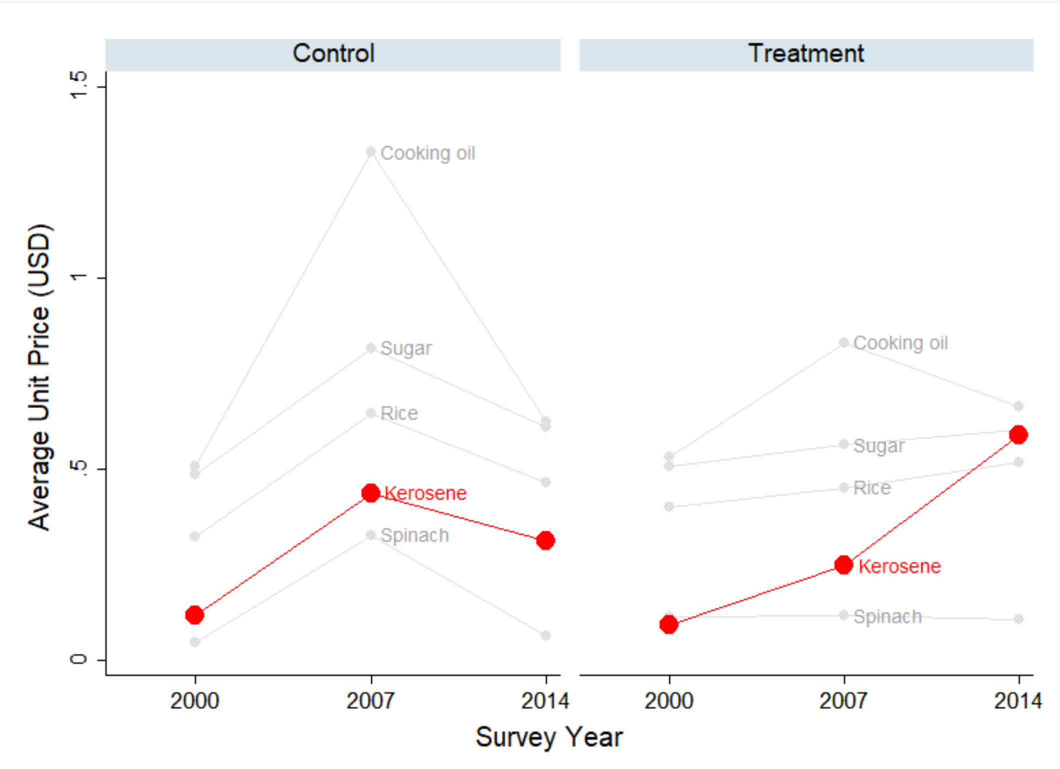
Figure 2: Percapita of kerosene consumption by primary cooking fuel



This figure plots the average percapita of kerosene consumption from the recent purchase by households' primary cooking fuel.

the effect of the policy. The program will impact only kerosene and LPG, in contrast to crisis which impact all commodities. Figure 3 shows that on the financial crisis year, prices for most of the commodities is increased in both treatment and control districts. But in 2014 and only in the treatment group, kerosene price doubled. While in the control groups, kerosene price follows the same trend with other commodities. The graphical evidence provides some support that the program of the program on kerosene is unique and distinct from the persistent effect of the crisis.

Figure 3: Trend of Kerosene Price in Treatment and Control group



This figure plots the average of CPI adjusted kerosene price per litre and other main household's food commodities. 1 USD = Rp 13,000.

6 Discussion

Considering the subsidized and the end-user energy equivalence, households switching to kerosene could potentially save about 30% of their cooking fuel cost, neglecting any potential rebound effect. I find that households reduce their kerosene consumption up to 100%. Household utility bills are reduced by 40%, 1.19 USD per month, on average. This response is statistically and economically significant, especially for the poor households. Fuel expenses takes about 30% of household utility bills, on average, with substantial heterogeneity across income brackets. I do not find any response to other nondurable expenditures which provides some evidence that, in this setting, consumption does not change in response to expected variations in fuel expenditure. Although this paper does not test any particular theoritical model, the results support rational expectation life-cycle theory which implies no spending response to a predictable change in anticipated changes in resources.

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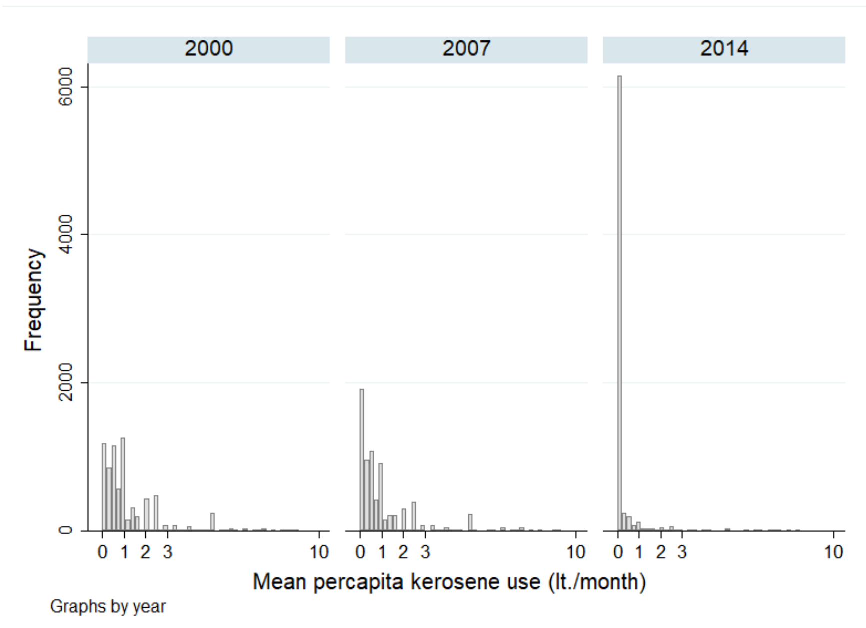
7 Appendix

Figure 4: Histogram of percapita kerosene consumption



This figure shows the distribution of households based on their percapita kerosene consumption on each survey wave.

Table 7.1: Test of parallel time trends

	(1) Percapita kerosene quantity (litre)	(2) Log kerosene price	(3) Log nondurables exp.	(4) Log food exp.	(5) Log utilities bills
ProgramX2007	-0.239	-0.008	0.213	0.146	0.004
	(0.491)	(0.175)	(0.249)	(0.142)	(0.119)
Constant	1.181	8.451***	11.754***	12.583***	10.767***
	(0.965)	(0.203)	(0.565)	(0.210)	(0.295)
Obs.	10,224	8,371	10,168	10,189	10,018
R^2 stat	0.512	0.903	0.710	0.702	0.802
Household FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y

Sample is prior to the program. All regressions include district fixed effects and year dummies. The standard error is clustered by district.

Table 7.2: Effect of the program on kerosene purchased, with alternative control groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Early vs Untreated		Late vs Untreated		Early vs Late Treated	
Panel A. Before the program						
ProgramX2007	0.171	-0.374	1.239	0.697	-0.331	-0.164
	(0.318)	(0.507)	(0.946)	(1.354)	(0.485)	(0.629)
Obs.	8,745	8,745	1,948	1,948	9,766	9,766
R^2 stat	0.036	0.514	0.029	0.506	0.034	0.511
Panel B. Full sample						
ProgamX2014	-1.596***	-1.775***	-1.643**	-1.965	-0.235	-0.062
	(0.499)	(0.659)	(0.646)	(1.412)	(0.295)	(0.360)
Obs.	13,003	13,003	2,886	2,886	14,517	14,517
R^2 stat	0.041	0.357	0.023	0.343	0.037	0.353
District FE	Y		Y		Y	
Household FE		Y		Y		Y
Month FE		Y		Y		Y

As the treatment group, column 1-2 and 5-6 use early treated households, and column 3-4 use late treated households. As the control group, column 1-4 use untreated households, and column 5-6 use late treated households. Panel A uses sample prior to the program to show pre-implementation trend between treatment and control groups. Panel B uses full sample to look at the program effect on the percapita kerosene quantity purchased (litre) (β_3 coefficient from Eq. 1). The standard error is cluster by district.